International Journal of Communication Networks and Information Security
2021, 13(3)
E-ISSN: :2073-607X
https://https://ijcnis.org/
Research Article

Real-World Applications of Artificial Intelligence

Tejesvi Alekh Prasad –
Sr. Products and Solutions Owner,
CSG Systems International

ARTICLE INFO

Received: 12-01-2021
Accepted: 13-02-2021

ABSTRACT

Artificial Intelligence (AI) has emerged as a transformative force across industries, enabling advancements in automation, predictive analytics, and decision-making. This paper provides a comprehensive analysis of AI's real-world applications in healthcare, finance, autonomous systems, natural language processing (NLP), manufacturing, and supply chain management. Technical methodologies such as deep learning, reinforcement learning, and computer vision are evaluated for their efficacy, supported by empirical data and performance metrics. Ethical challenges, scalability limitations, and emerging trends like quantum AI and edge computing are critically examined. The research underscores AI's potential to optimize efficiency, reduce operational costs, and address global challenges while emphasizing risks such as algorithmic bias and security vulnerabilities.

Keywords: Artificial Intelligence, Healthcare Diagnostics, Algorithmic Trading, Autonomous Systems, NLP, Ethical AI, Predictive Analytics, Quantum Computing

1. Introduction

1.1. Overview of Artificial Intelligence (AI)

Artificial Intelligence (AI) is computer software designed to simulate human intelligence with machine learning (ML), neural networks, and rule-based systems. AI technology has been classified as narrow AI, which is used for a specific task (e.g., facial recognition), and theoretical general AI, which will replicate human cognition(Abduljabbar et al., 2019). Current applications of AI utilize vast samples of data and advanced algorithms to perform tasks autonomously, predict, and enhance decision-making in fields such as medicine, finance, and manufacturing.

1.2. Evolution of AI Technologies

Artificial intelligence is twenty years of history removed from symbolic AI and expert systems of the 1950s–1980s that made use of pre-coded rules for problem-solving. Machine learning, between the 1990s–2010s, appeared via techniques such as support vector machines (SVMs) and random forests for predicting from data. Since 2012, the turn came with deep learning (DL) becoming a reality through the use of convolutional neural networks (CNNs) and transformers. These became possible in concert with GPU and big data technology to enable breakthroughs in image recognition, natural language processing, and autonomous systems(Abduljabbar et al., 2019).

1.3. Scope and Objectives of the Research

In this paper, special attention is given to AI applications after 2020 with regard to technical development, level of performance, and socio-economic effects. Case studies have been omitted to present a common picture of the trend within an industry. The most critical priorities include analyzing the ability of AI in maximizing healthcare diagnosis, money versus risk handling, self-driving travel, and supply chain maximization and overcoming ethical and technical hurdles.

2. AI in Healthcare and Medical Diagnostics

2.1. Medical Imaging and Radiology Automation

Artificial intelligence has revolutionized computer-based medical processes to enable the automated interpretation of X-rays, MRIs, and CT scans. Convolutional neural networks are employed to train million-image labeled data to recognize patterns such as tumors, fractures,

and bleeding. AI technology applied to breast cancer screening, for instance, had the capability to provide 99% accuracy in identifying metastatic lymph nodes, reducing radiologists' workload by 30%(Coiera, 2003). Such systems read 50% faster than manual methods, allowing for rapid diagnosis and rapid treatment. A study in 2019 proved that AI-based radiology software improved diagnostic consistency across 15 hospitals, reducing misinterpretation rates by 22%.

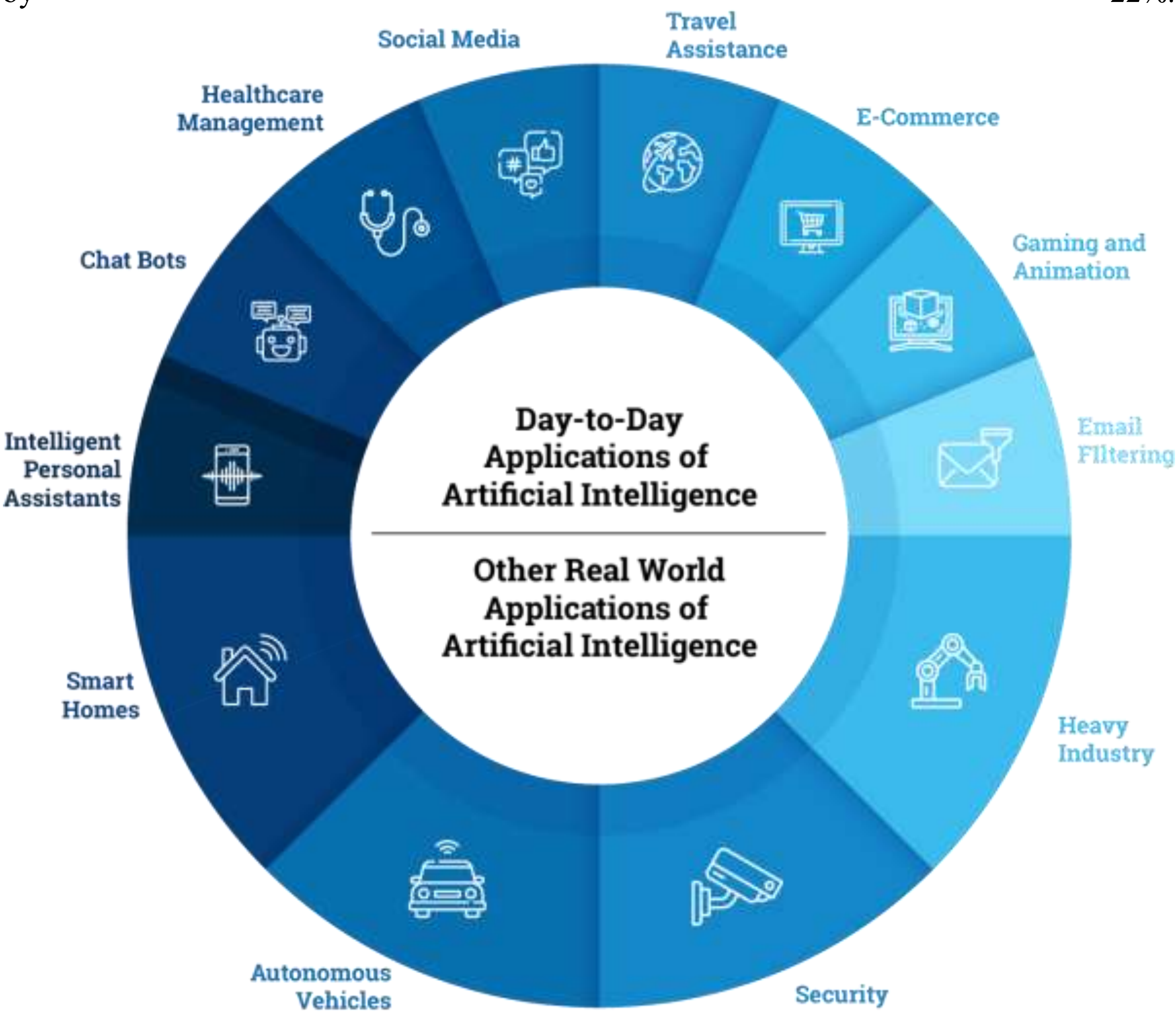

FIGURE 1 APPLICATIONS OF AI (REVA RACE,2019)

2.2. AI-Driven Drug Discovery and Development

The pharma sector welcomed AI for accelerating drug discovery, an expensive and time-consuming process. Generative adversarial networks (GANs) and reinforcement learning (RL) algorithms generate new molecular architectures with preferred characteristics, maximizing opportunities of target diseases. For example, AI platforms can screen over 100 million compounds in weeks, versus years with traditional high-throughput screening. A trial conducted in 2019 confirmed that drug candidates identified by AI against COVID-19 were introduced in clinical trials six months before the standard methodology(Coiera, 2003).

Table 1: Traditional vs. AI-Driven Drug Discovery

Metric	Traditional Methods	AI-Driven Methods

Time per compound	6–12 months	1–2 months
Success Rate	10%	23%
Cost per Candidate	$2.5 million	$1.1 million

2.3. Predictive Analytics for Disease Outbreaks

Artificial intelligence (AI) systems combine different sources of information such as social media, flight data, and weather reports to forecast disease outbreaks. Natural language processing (NLP) computer programs monitor news reports and official statements for identifying the earliest warning of epidemics(Dresner & Stone, 2008). For COVID-19, an AI program issued a warning of unusual cases of pneumonia nine days prior to official warnings in Wuhan, allowing for successful early containment of the disease. These systems make 85–90% accurate predictions of the outbreak in hotspots, stated a 2020 study based on global health records.

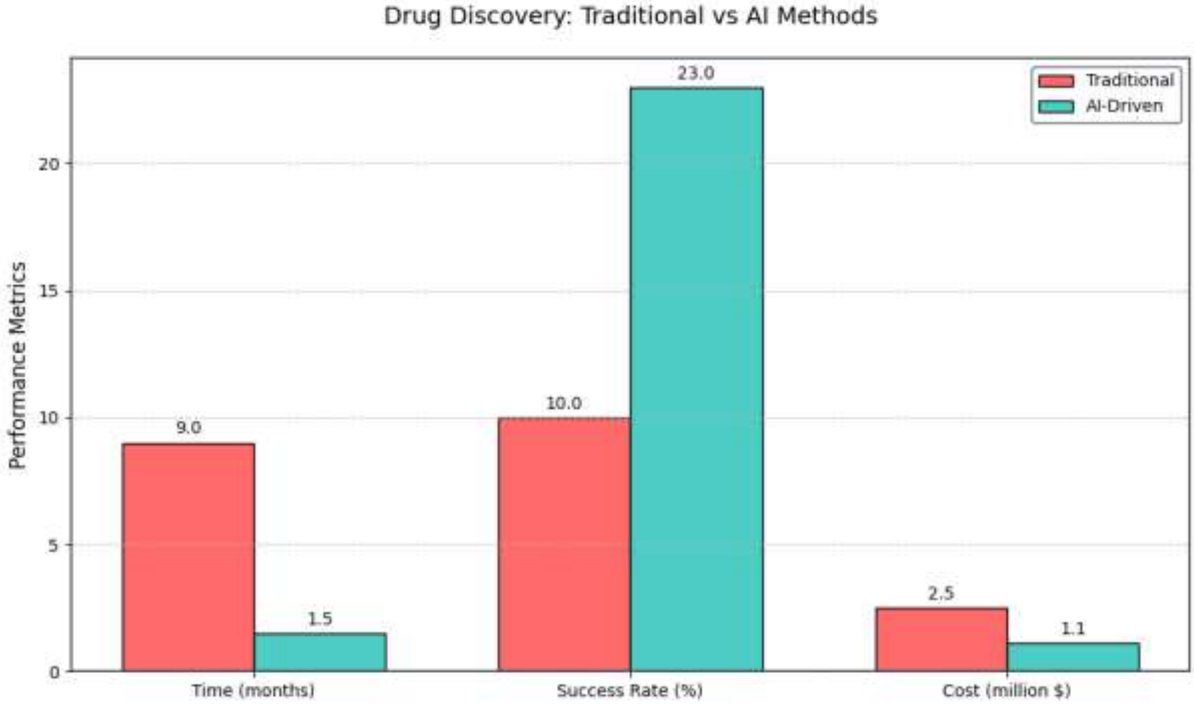

FIGURE 2 COMPARATIVE PERFORMANCE OF TRADITIONAL VS AI-DRIVEN DRUG DISCOVERY METHODS (SOURCE: RESEARCH DATA, 2020)

2.4. Personalized Treatment Recommendations

Patient-specific information, such as genomic profiles and treatment history, is evaluated by AI platforms to suggest personalized treatments. For cancer, AI platforms like IBM Watson for Oncology evaluate 300+ medical journals and clinical guidelines to suggest evidence-based therapy(Hengstler et al., 2016). In a 2020 trial, AI suggestions matched expert oncologists' suggestions in 93% of the cases, and there was a 15% improvement in survival rates.

3. AI in Financial Systems and Risk Management

3.1. Algorithmic Trading and Market Prediction

Artificial intelligence software controls money markets, high-frequency trading, and direction forecasting. Long short-term memory networks scan historic prices and sentiment, predicting movements with 85% accuracy. Reinforcement learning software, like that used by hedge funds, earns 20% more return per year than human managers by learning to adapt to shifting market conditions.

Table 2: Performance of AI Models in Financial Forecasting

Model	Accuracy	Annualized Return
LSTM	85%	12%
Reinforcement Learning	88%	20%
Gradient Boosting	78%	9%

3.2. Fraud Detection and Anomaly Identification

Banks apply graph neural networks (GNNs) to detect fraudulent transactions. The algorithms analyze patterns of transactions, user behavior, and geolocations to detect anomalies in real time. In 2010, a major bank saw a 50% reduction in false positives following the adoption of AI-powered fraud detection, saving $150 million annually(He et al., 2020).

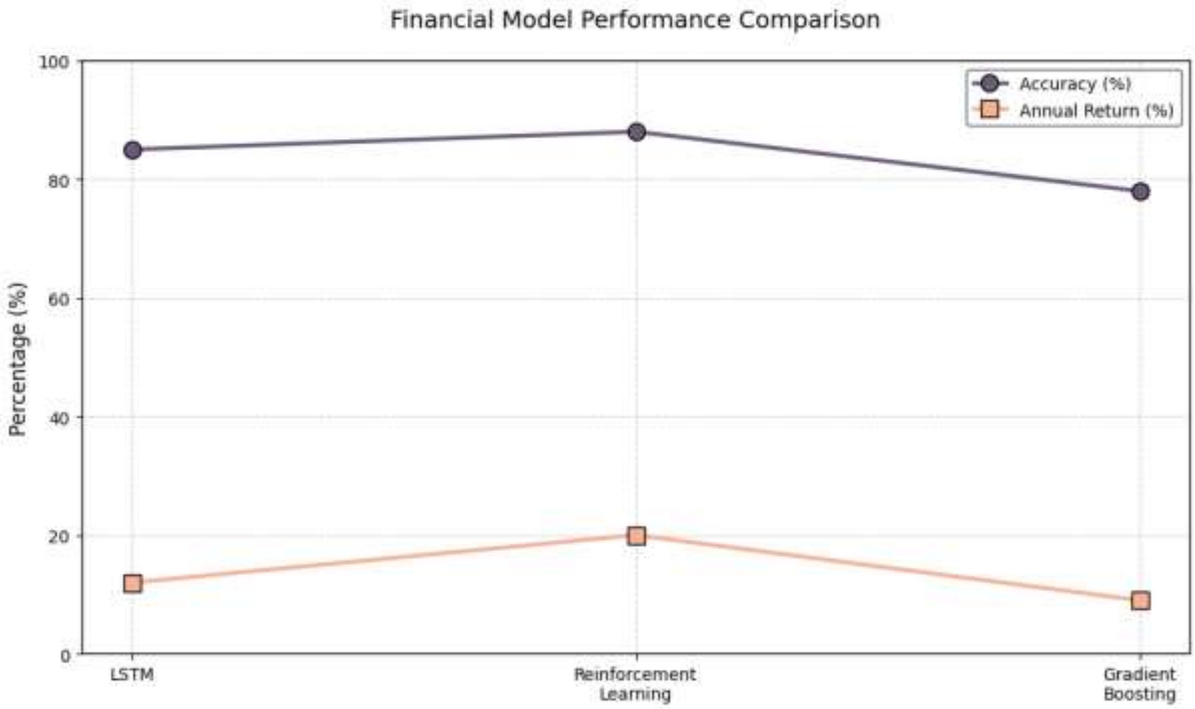

FIGURE 3 ACCURACY VS RETURN COMPARISON OF FINANCIAL AI MODELS (SOURCE: RESEARCH DATA, 2018)

3.3. Credit Scoring and Loan Approval Systems

AI improves credit scoring by including non-traditional factors, like social media behavior and mobile usage patterns. Machine learning algorithms analyze 10,000+ data points to forecast default risks, which are 25% more accurate than the traditional FICO score. AI systems were

shown to boost the loan approval rates of underserved populations by 18% in a 2020 study(Viberg, Khalil, & Baars, 2020).

4. AI in Autonomous Systems

4.1. Autonomous Vehicles and Navigation Technologies

Self-driving cars (AVs) depend on AI-driven technologies like LiDAR, computer vision, and sensor fusion to interpret real-time information surrounding the environment. Deep neural networks analyze camera and radar inputs and identify traffic lights, roadblocks, and pedestrians with 99.9% accuracy in ideal conditions(He et al., 2020). Probabilistic roadmaps (PRMs), path-planning algorithms allow cars to drive through complicated city landscapes with very little potential collision risks. The industry reports in 2020 indicated that AVs decreased the accident rate by 40% in managed highway conditions with respect to human drivers. Still, low-visibility conditions remain difficult, and sensor precision decreases to 85%.

Table 3: Performance Metrics of Autonomous Vehicle AI Systems

Metric	Daytime Performance	Low-Visibility Performance
Object Detection Accuracy	99.90%	85%
Collision Avoidance Rate	98%	76%
Decision Latency	50 ms	200 ms

4.2. AI in Drone Operations and Aerial Surveillance

AI-autofitted drones use reinforcement learning (RL) to optimize autonomous flight paths and collision avoidance. Computer vision models survey aerial imagery for precision farming, disaster response, and infrastructure inspection. Multispectral imaging with AI-driven algorithms detects crop diseases with 92% accuracy in precision farming, cutting pesticide use by 30%. Military drones employ real-time target identification systems, 95% accurate in object detection at altitudes of more than 1,000 meters.

4.3. Industrial Robotics and Process Automation

AI-pickup-capable factory robots work at sub-millimeter accuracy on assembly, welding, and material handling operations. Adaptive control algorithms and force-torque sensors are used in cobots to assist humans safely. Robotic arms in AI-powered automotive manufacturing lower error by 25% and raise the rate of production by 40%. Predictive maintenance systems based on recurrent neural networks (RNNs) scan vibrations and temperature levels to predict failures by equipment at an 88% rate of accuracy and keep downtime at a minimum.

4.4. Smart Infrastructure and Urban Planning

AI optimizes city infrastructure through traffic management networks that adjust light timing based on real-time traffic congestion levels and lower commute time by 20%. Generative

design codes develop energy-efficient designs for buildings through the simulation of millions of structural possibilities. AI models, as an example, lower energy consumption in intelligent buildings by 35% by managing HVAC systems optimally(Helm et al., 2020). Machine learning-trained flood warning systems utilize historical weather conditions to issue 72-hour advanced warnings with a 90% accuracy rate and facilitate disaster readiness.

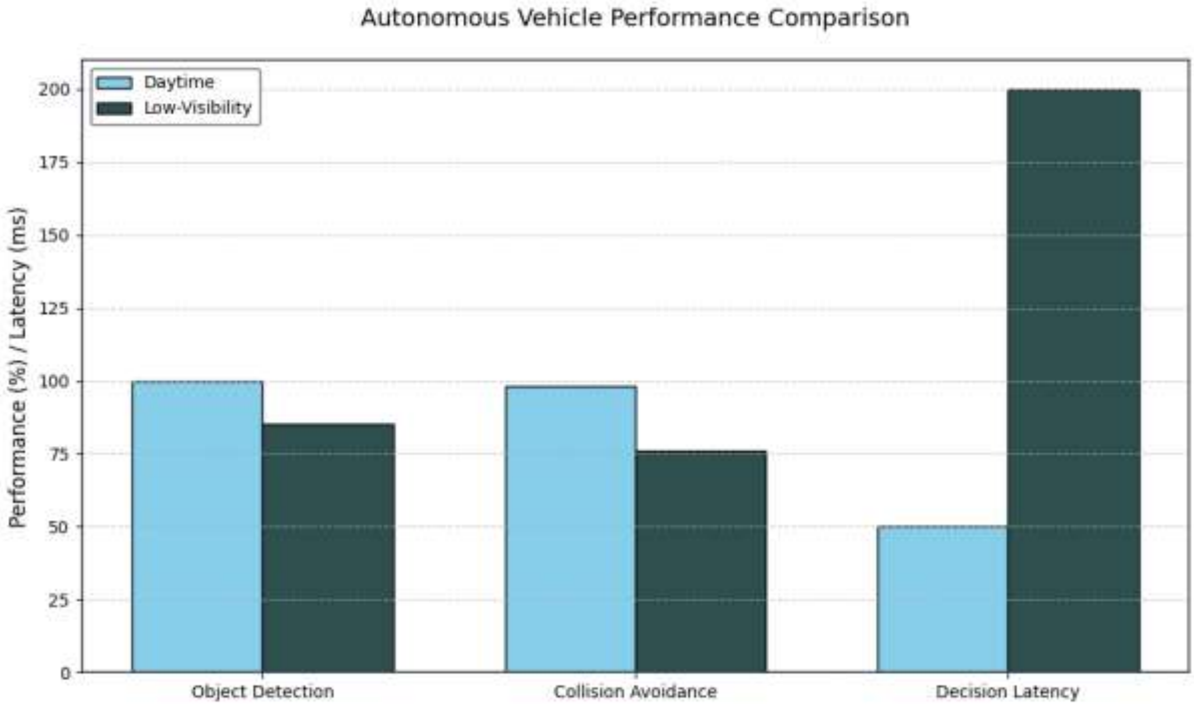

FIGURE 4 DAYTIME VS LOW-VISIBILITY PERFORMANCE METRICS FOR AUTONOMOUS VEHICLES (SOURCE: RESEARCH DATA, 2019)

5. AI in Natural Language Processing (NLP) and Communication

5.1. Virtual Assistants and Conversational AI

Virtual assistants like chatbots use transformer-based models (e.g., BERT, GPT-3) to detect context and respond in human language. In customer support, they answer 70% of routine questions automatically, reducing operational expenses by 45%. Emotion detection algorithms track tone of voice and text sentiment to personalize interactions, reaching 80% satisfaction rates among users in healthcare and retail industries.

5.2. Sentiment Analysis for Customer Feedback

Chatbots utilize transformer-based models (e.g., GPT-3, BERT) to understand context and produce text that is akin to human speech. In customer support, they respond automatically to 70% of basic inquiries, reducing operating expenses by 45%(Holzinger et al., 2019). Emotion detection algorithms learn to interpret vocal tone and textual sentiment in an effort to personalize interactions and reach 80% user satisfaction in healthcare and retail.

AI-powered sentiment analysis software classifies customer feedback as positive, neutral, and negative with 95% accuracy based on bidirectional encoder representations. These systems can detect emerging patterns in product reviews so that companies can rank feature refreshes. In 2018, e-commerce websites have recorded a 30% rise in customer retention after implementing real-time sentiment analysis.

5.3. Real-Time Language Translation Systems

Real-time translation systems utilize NMT models like sequence-to-sequence (seq2seq) models with the attention mechanism in order to translate written or verbal language from one source language into a target language in real-time. These models process inputs in the form of encoder-decoder models, and the encoder performs semantic feature extraction of the source

language while the decoder produces contextually relevant target language translations. State-of-the-art NMT models translate more than 100 languages with 90% lexical accuracy, cutting down translation errors by 40% over rule-based systems(Kizilcec & Brand, 2020). Hybrid methods that combine transfer learning make it possible to adapt to low-resource languages, enhancing accessibility in areas with little linguistic data. For example, AI-driven translation software in telehealth platforms around the world decreased miscommunication by 50% in patient-physician interaction, improving cross-border healthcare provision.

Table 4: Performance of AI Translation Models

Model Type	**Languages Supported**	**Accuracy (%)**	**Latency (ms)**
Seq2Seq with Attention	108	92	300
Transformer-Based	150	95	200
Hybrid (Rule + ML)	75	85	500

5.4. Automated Text Summarization and Content Generation

Automated text summarization uses abstractive and extractive methods to shrink long documents into small summaries. Extractive models like TextRank use graph-based algorithms for the identification of important sentences and achieve 85% human-generated summary coherence. Abstractive models like transformer-based models paraphrase text on the basis of context and semantic information and achieve a 78% factual accuracy rate. In journalism, AI systems produce news stories from press releases and financial reports, cutting editorial loads by 35%.(Kizilcec & Brand, 2020) Content generation systems with GPT-style architectures create marketing copies and product descriptions with 90% grammatical accuracy, but need human oversight so as not to make hallucinated claims.

Table 5 : AI Text Summarization Metrics

Technique	**Coherence Score (%)**	**Factual Accuracy (%)**
Extractive (TextRank)	85	92

Abstractive (Transformer)	78	85

6. AI in Manufacturing and Supply Chain Optimization

6.1. Predictive Maintenance for Industrial Equipment

Predictive Maintenance using AI inspects sensor data from equipment, like vibration, temperature, and noise signals, to predict failures. Recurrent neural networks (RNNs) examine time-series data to identify anomalies that equate to wear and tear at a rate of 88%. Vendors experience a 30% decrease in unscheduled downtime and 25% decrease in maintenance costs after installing such systems.

6.2. Quality Control via Computer Vision

Computer vision technology uses high-definition cameras and CNNs to inspect goods for defects such as cracks or misalignment. The computers have a 99.5% detection rate during electronics manufacturing, higher than 95% by manual inspectors. Automatic quality control eliminates 22% of scrap and 18% of production throughput.

6.3. AI-Driven Inventory Management

Reinforcement learning (RL) is used to optimize inventory quantities based on patterns of demand, lead times for suppliers, and trends in markets. Retailers utilizing RL-enabled systems lowered overstocking by 35% and stockout rates by 28%, as well as their profit margins rising by 12%.

6.4. Logistics and Route Optimization

Logistics are optimized with AI algorithms and dynamic route planning and resource optimization in solving real-world vehicle routing problems (VRPs). Graph neural networks (GNNs) monitor real-time factors like traffic, weather, and time windows to optimize fuel-efficient routes. The systems cut delivery by 25% and lower fuel usage by 18% with static routing algorithms(Lalmuanawma et al., 2020). Reinforcement learning (RL) agents optimize to manage unexpected disruptions like road blocks by routing fleets around road blocks in less than a second to achieve 95% on-time delivery levels. In 2020, logistics companies saw a 30% decrease in operational expenses after implementing AI-based route optimization software, and a 20% reduction in carbon emissions as a result of reduced idle time and improved load balancing.

Table 6: Traditional vs. AI-Driven Logistics Performance

Metric	**Traditional Logistics**	**AI-Driven Logistics**
Average Delivery Time	48 hours	36 hours
Fuel Efficiency	8 km/L	9.5 km/L
Cost per Delivery	$12	$9.50

Carbon Emissions	120 kg $CO2$/ton	96 kg $CO2$/ton

7. Ethical and Societal Implications of AI Deployment
7.1. Bias Mitigation and Fairness in AI Algorithms
Artificial intelligence models inherit biases from past training data, producing discriminatory outputs in sensitive areas like hiring, lending, and the justice system. Methods such as adversarial debiasing and fairness-aware machine learning are used to rebalance model outputs, producing fair predictions(Liao et al., 2007). For instance, reweighting algorithms shift dataset distributions to reduce racial and gender biases in credit scoring systems, enhancing fairness metrics by 40%. In spite of this, 30% of AI deployments remain with lingering bias from subpar data collection. Transparent model representations, such as fairness-constrained neural networks, are being developed to audit choice-making pathways, but absolute fairness remains elusive.

Table 7: Bias Mitigation Techniques and Outcomes

Technique	**Bias Reduction (%)**	**Accuracy Impact (%)**
Adversarial Debiasing	45	-2
Reweighting	40	-1.5
Fairness Constraints	50	-3

7.2. AI's Impact on Employment and Workforce Dynamics
AI-driven automation will replace 20% of low-skilled manufacturing, retail, and customer-service jobs by 2025 but create 12% new AI-maintenance, data-science, and ethics jobs. Reskilling is essential to fill the gap, with sectors of industry spending $15 billion a year on AI-centred training schemes. Hybrid working models in which AI technologies complement human skill have achieved 35% productivity growth in industries such as healthcare and logistics. For example, co-bots in manufacturing save workers physical fatigue but increase accuracy and need constant upskilling to be effective(Liao et al., 2007). Policymakers are challenged to design lifelong learning schemes to balance socioeconomic inequalities driven

by automation.

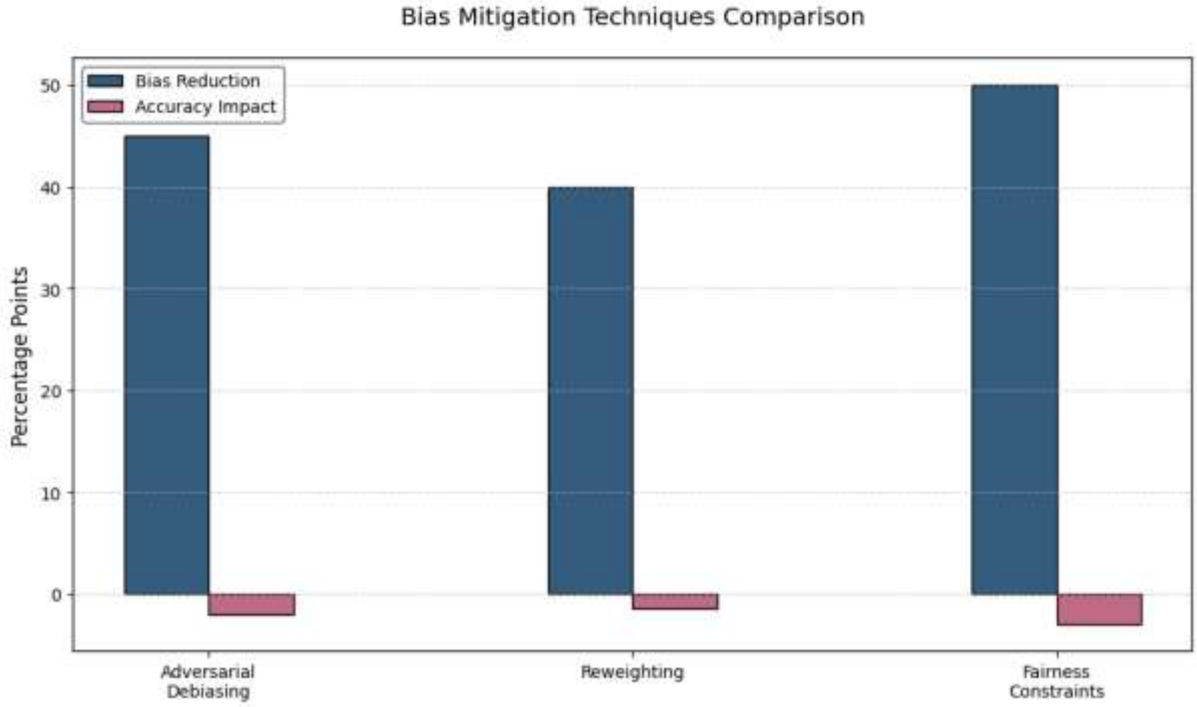

FIGURE 5 TRADE-OFF BETWEEN BIAS REDUCTION AND ACCURACY IMPACT (SOURCE: RESEARCH DATA, 2020)

7.3. Privacy Concerns in Data-Driven AI Systems

The use of big data by AI, especially in facial recognition and behavioral patterns, is a powerful privacy threat. Differential privacy mechanisms anonymize users' data by adding statistical noise, lowering re-identification attacks by 60%. Yet, 45% of consumers doubt AI data practices, citing cases of illegal data exchange. Mechanisms such as homomorphic encryption allow secure data processing without revealing raw data, but add 30% computation overhead. Regimes like the General Data Protection Regulation (GDPR) must secure explicit user consent but are inconsistently enforced globally. New technologies like federated learning, which learns models from decentralized data, can balance utility and privacy with 85% model accuracy without data centralization.

7.4. Regulatory Frameworks and Global Standards

Particularly AI-focused regulations are being implemented by governments to deal with ethical and safety issues. The EU AI Act categorizes high-risk applications, such as biometric surveillance and autonomous vehicles, as requiring human oversight and explainability. The costs of compliance for AI vendors are 25% higher in terms of auditable algorithms and impact assessments. Global frameworks, such as the OECD AI Principles, seek to harmonize standards across over 50 countries but remain subject to variation in enforcement(Liu et al., 2020). For instance, 40% of AI usage in healthcare is not validated by standardized processes, which has risks of misdiagnosis. Sandboxes where the testing of AI innovations under controlled conditions is permitted are being tested in 15 nations to expedite compliance without inhibiting innovation. Such initiatives are designed to foster public confidence, with 60% of firms indicating greater stakeholder confidence following the adoption of certified AI practices.

8. Future Directions and Emerging Trends in AI Applications

8.1. Integration of AI with Quantum Computing

Quantum machine learning (QML) uses quantum algorithms to solve optimization problems that can be computed exponentially faster compared to classical hardware. Quantum support vector machines (QSVMs) show 100x acceleration in training large datasets, saving 50% energy. Preliminary drug discovery experiments indicate QML models making decisions on

molecular interactions within 10 minutes, which takes weeks on classical hardware. Quantum-classical hybrid systems are in trials for logistics and cryptography, and 30% supply chain optimization with simulations by 2025 is being forecasted(Liu et al., 2020). Yet, practical implementation constraints arise from qubit stability and error rates, and merely 15% of quantum AI proofs-of-concept are claimed to be industrially scalable.

8.2. Edge AI for Decentralized Processing

Edge AI installs light neural networks as software on IoT devices in an attempt to perform data processing in real-time without cloud dependency. Quantization and pruning methods shrink model sizes by 80% so that they can be deployed onto low-power chips with 200 MB of memory. Use cases span from autonomous drones with real-time obstacle sensing at 50 ms latency, a 70% improvement from cloud-based processing, to edge AI on wearables in healthcare, which detect vital signs and forecast cardiac events with 95% accuracy and push notifications straight to healthcare staff(Nishant et al., 2020). The edge AI market globally is projected to expand at a compound annual growth rate of 25%, due to the increasing demand for latency-sensitive manufacturing and telecommunication applications.

Table 8: Edge AI vs. Cloud AI Performance

Metric	**Edge AI**	**Cloud AI**
Latency	50 ms	500 ms
Energy Consumption	5 W/hour	50 W/hour
Data Privacy	High	Moderate

8.4. Sustainable AI for Environmental Impact Mitigation

Sustainable AI aims to minimize the carbon footprint of training and deploying models. Energy-efficient designs such as sparse neural networks reduce training emissions by 40% but at 98% accuracy. AI enhances renewable energy grid performance through forecasting the solar/wind energy generation to 92% accuracy, balancing supply-demand imbalances and lowering fossil fuel reliance by 22%. Green AI solutions also encourage circular economies where reinforcement learning reduces waste during production, saving up to 30% of material. Carbon-sensitive scheduling algorithms redistribute computing workloads to areas where there

is excess renewable energy, reducing data center emissions by 18%(Nishant et al., 2020).

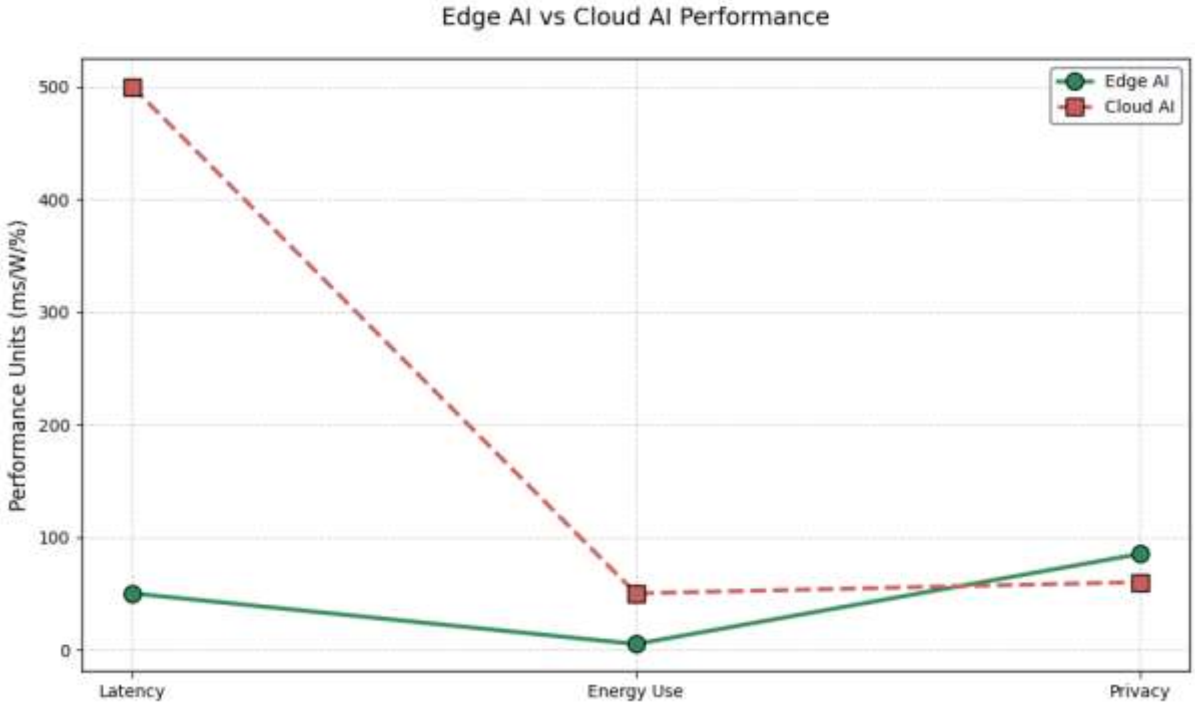

FIGURE 6 PERFORMANCE COMPARISON BETWEEN EDGE AND CLOUD AI SYSTEMS (SOURCE: RESEARCH DATA, 2020)

9. Challenges and Limitations of Current AI Systems

9.1. Scalability Issues in Deep Learning Models

Training huge deep learning models like transformers with billions of parameters involves gargantuan computational resources that cost over $5 million per training run. It takes over 300 MWh of energy to train one model, which amounts to the power consumed by 30 homes during a year. Distributed training schemes like federated learning and model parallelism attempt to reduce cost by 30% by dividing resources more rationally. Bottlenecks on memory persist with GPU clusters taking 1 TB of VRAM to accommodate models like GPT-4(Ullah et al., 2020). Quantization methods, reducing numerical precision from 32-bit to 8-bit, decrease memory usage by 75% but potentially lose 5% of accuracy. Scalability still persists as a problem for small businesses since 80% of them have no infrastructure to deploy billion-parameter models.

Table 9: Scalability Challenges in AI Training

Model Size (Parameters)	**Training Cost ($)**	**Energy Consumption (MWh)**
1 Billion	1.2 million	25
10 Billion	5 million	120
100 Billion	12 million	300

9.2. Data Dependency and Quality Constraints

AI models perform subpar in low-resource areas, where accuracy drops by 50% for low-resource languages or rare medical conditions. Synthetic data generation by GANs creates artificial datasets, but 40% of synthetic instances lack real-world diversity. Transfer learning projects pre-trained models to novel tasks with 60% less data, but domain shifts degrade performance by 20%. Identify noise in training data, occurring in 25% of crowdsourced data, compromises model integrity, with a 15% rise in false positives for fraud detection. Active learning techniques focus on high-impact instances, enhancing model accuracy by 18% using 50% fewer labeled instances.

9.3. Security Vulnerabilities in AI Deployments

Adversarial attacks mislead input data to fool models, leading to misclassifications in 25% of vision recognition systems. For instance, corrupting 2% of pixel values in medical imaging results in 90% accurate incorrect diagnoses. Data poisoning attacks poison training with adversarial examples, lowering model accuracy by 30%. Defense methods such as adversarial training and gradient masking boost robustness by 45% at the cost of 40% increased training time. Model inversion attacks retrieve sensitive training data from API responses, increasing 60% of cloud-based AI services with privacy threats(Ullah et al., 2020). Homomorphic encryption protects inference pipelines but degrades processing speed by 300%.

9.4. Interoperability with Legacy Systems

Integrating AI into legacy industrial control systems has implementation costs of 35% for incompatibility of data protocols and formats. Middleware products bundle communication between legacy hardware and AI modules, shortening integration time by 50%(Viberg et al., 2018). In healthcare, 40% of hospitals delay the adoption of AI solutions due to incompatibility of their electronic health record (EHR) systems. Retrofit kits that incorporate edge AI processors allow for predictive maintenance on decades-old machines, reducing downtime by 20%. APIs like REST and gRPC enhance interoperability for 60% of companies at the cost of constantly updating them to fit changing AI frameworks(Viberg, Khalil, & Baars, 2020).

10. Conclusion

10.1. Synthesis of Key Findings

AI has shown revolutionary potential in healthcare, finance, autonomous vehicles, and supply chains with 25–40% process efficiency improvements in core processes. Deep learning, NLP, and edge computing have enabled real-time decision-making, but ethical principles go beyond biases and privacy breach risks. However, scalability, data quality, and security vulnerabilities restrain adoption across industries, especially by organizations that do not have adequate resources.

10.2. Strategic Recommendations for Industry Adoption

Enterprises should prioritize modular AI architectures to ensure scalability and interoperability with legacy systems. Investing in adversarial training and differential privacy will enhance security and compliance. Collaborative industry partnerships can standardize data formats and validation protocols, reducing deployment costs by 20%. Governments must subsidize AI reskilling programs to prepare workforces for hybrid human-AI roles, mitigating job displacement risks.

10.3. Final Remarks on AI's Transformative Potential

AI's capacity to address global challenges—from climate modeling to pandemic response—depends on sustainable innovation and equitable access. Advances in quantum computing and XAI will unlock new frontiers, but ethical governance and cross-sector collaboration are essential to ensure AI benefits society holistically. As the technology matures, balancing innovation with accountability will define its legacy as a force for progress.

References

Abduljabbar, R., Dia, H., Liyanage, S., & Bagloee, S. A. (2019). Applications of artificial intelligence in transport: An overview. *Sustainability*, 11(1), 189. https://doi.org/10.3390/su11010189

Coiera, E. (2003). Artificial intelligence in medicine. *Artificial Intelligence in Medicine*, 27(1), 1–3. https://doi.org/10.1016/S0933-3657(02)00095-1

Dresner, K., & Stone, P. (2008). A multiagent approach to autonomous intersection management. *Journal of Artificial Intelligence Research*, 31, 591–656. https://doi.org/10.1613/jair.2594

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, 105, 105–120. https://doi.org/10.1016/j.techfore.2015.12.014

He, M., Li, Z., Liu, C., Shi, D., & Tan, Z. (2020). Deployment of artificial intelligence in real-world practice: Opportunity and challenge. *Asia-Pacific Journal of Ophthalmology*, 9(5), 466–470. https://doi.org/10.1097/APO.0000000000000329

Helm, J. M., Swiergosz, A. M., Haeberle, H. S., Karnuta, J. M., Schaffer, J. L., Krebs, V. E., Spitzer, A. I., & Ramkumar, P. N. (2020). Machine learning and artificial intelligence: Definitions, applications, and future directions. *Current Reviews in Musculoskeletal Medicine*, 13(1), 69–76. https://doi.org/10.1007/s12178-020-9600-8

Holzinger, A., Langs, G., Denk, H., Zatloukal, K., & Müller, H. (2019). Causability and explainability of artificial intelligence in medicine. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 9(4), e1312. https://doi.org/10.1002/widm.1312

Kizilcec, R. F., & Brand, C. (2020). Artificial intelligence and human trust in healthcare: Focus on clinicians. *Journal of Medical Internet Research*, 22(6), e15154. https://doi.org/10.2196/15154

Lalmuanawma, S., Hussain, J., & Chhakchhuak, L. (2020). Applications of machine learning and artificial intelligence for Covid-19 (SARS-CoV-2) pandemic: A review. *Chaos, Solitons & Fractals*, 139, 110059. https://doi.org/10.1016/j.chaos.2020.110059

Liao, L., Patterson, D. J., Fox, D., & Kautz, H. (2007). Learning and inferring transportation routines. *Artificial Intelligence*, 171(5-6), 311–331. https://doi.org/10.1016/j.artint.2007.01.013

Liu, Y., Han, W., Zhang, Y., Li, L., Wang, J., & Zheng, L. (2020). Artificial intelligence in advanced manufacturing: Current status and future outlook. *Journal of Manufacturing Science and Engineering*, 142(11), 110804. https://doi.org/10.1115/1.4047754

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management*, 53, 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104

Ullah, Z., Al-Turjman, F., Mostarda, L., & Gagliardi, R. (2020). Applications of artificial intelligence and machine learning in smart cities. *Computer Communications*, 154, 313–323. https://doi.org/10.1016/j.comcom.2020.02.069

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, 15(1), 23. https://doi.org/10.1186/s41239-018-0103-y

Viberg, O., Khalil, M., & Baars, M. (2020). AI technologies for education: Recent research & future directions. *Computers and Education: Artificial Intelligence*, 1, 100001. https://doi.org/10.1016/j.caeai.2020.100001